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Automatic Classification of Focal Lesions in Ultrasound Liver Images using Principal Component Analysis and Neural Networks

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***Abstract*— Ultrasound Medical Imaging is currently the most popular modality for diagnostic application. This imaging technique has been used for the detecting abnormalities associated with abdominal organs like liver, kidney, uterus etc. In this paper, the possibilities of automatic classification of the ultrasound liver images into four classes–Normal, Cyst, Benign and Malignant masses, using texture features are explored. These texture features are extracted using the various statistical and spectral methods. The optimal feature selection process is carried out manually to pick the best discriminating features from the extracted texture parameters. Also, the method of principal component analysis is used to extract the principal features or directions of maximum information from the data set there by automatically selecting the optimal features. Using these optimal features, a final combined feature set is formed and is employed for classification of the liver lesions into respective classes. K-means clustering and neural network based automatic classifiers are employed in this process. The classifier design and its performance are studied. This paper summarizes the various statistical and spectral texture parameter extraction processes, optimal feature selection techniques and automated classification procedures involved in our work.**

Keywords: Texture, Image analysis, Feature Extraction, Feature selection, Classification, Principal Component Analysis, Neural Networks.

I. Introduction

THE ultrasound medical imaging modality is generally used for visualizing the various organs and soft tissues. It enables the operator to select the right image plane to display the pathological anatomy accurately in the organs like the liver, kidney, pancreas etc [1]. The main advantage of ultrasound medical imaging is that it is non-radiological, non-invasive and cost effective [2].

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Ultrasonic echoes from human tissues are displayed as B-scan images, which form texture patterns that are characteristics of both the imaging system and the tissue that is being imaged [3], [4].

Liver imaging has been one major application of the diagnostic ultrasound, which is helpful in early detection of fatal liver diseases. Unlike the diffused liver diseases, the focal diseases such as cysts and tumors are concentrated over a small area of the tissue and it is very difficult to identify the diseased part from the image alone, hence a biopsy test is needed to confirm the disease. To reduce the number of post biopsy hemorrhages, an early non-invasive detection mechanism that identifies the different types of focal lesions from the digitized medical ultrasound image should be clinically feasible. The focal lesions are clinically differentiated based on the echo texture patterns and hence texture analysis is considered efficient. Texture analysis methods are broadly classified as statistical, structural, model and spectral methods [5]. Out of these, the statistical and spectral methods are most suited to analyze the global and local texture information in the image. For example, homogeneity and regularity have been used as essential parameters for efficiently segmenting the cystic lesion area from the ultrasound image [6]. On reviewing the various approaches and models of texture, some of the best statistical and spectral methods of feature extraction are: the second order inter pixel relationship matrix known as grey level co-occurrence matrix (GLCM), the grey-level run-length matrices (GLRLM), Laws 2D filters and wavelet transform based filter banks [7], [8], [9], [10], [11], [12]. Though these algorithms have offered much higher classification rate on computed tomographic (CT) images [13] of better contrast and clear visualization than the ultrasound images, yet more research has been initiated in the field of ultrasound since they are non-radiological, non-invasive and less harmful.

Previous works suggest algorithms for extracting new and significant texture features for differentiating the normal liver from diseased lesion [8], [12]. But the optimal features describing the region of interest (ROI) have to be identified for efficient classification. Feature selection procedures like simple manual search, Hotelling trace parameters, and genetic algorithmic search techniques have been proposed earlier. The algorithms like the GLCM and GLRLM yields large number of features wherein it is difficult to select optimal feature manually. Hence we go for an automatic

feature selection process known as principal component analysis (PCA), which retains only the most significant feature from the n-dimensional feature space. This method is considered best for data clustering in multivariate problems [14]. The resultant reduced transformed features are clustered into their respective classes using an unsupervised method like the k-means clustering [15]. Meanwhile, selecting the best features manually has also yielded good results. For this combined optimal feature set, the Back-Propagation networks (BPN) based supervised pattern recognition process has been most efficient [9], [12], [16].

In this paper, 4 algorithms such as Laws method, Gabor wavelet based filtering; GLCM and GLRLM methods are used to extract the various texture features. For each of the feature set, optimal feature selection is carried out using manual search and automated PCA technique. K-means clustering is used to classify the PCA based combined features and a BPN classifier is used to classify the manually selected combined features. The correct classification rate is used to evaluate the performance of the two classifiers in classifying the lesion types.

II. Materials and Methods

In this study, the liver lesion images are collected from the MEDISCAN SYSTEMS, CHENNAI, TAMILNADU, INDIA on various patients taken using the ATL HDI 5000 ultrasound machine using curvilinear and sector transducer array at a frequency 4 MHz. The digital JPEG image is of 8-bit resolution. The cysts and tumors occur single or multiple and are generally less than 10 centimeters fitting into a grid size of 80x80 pixels. The lesions are segmented and from the center of the ROI small rectangular grid of size 10X10 pixels are used as test region to localize the lesion and to reduce the number of false positives during classification process. The sample images each class is shown in Fig 1 after removing the patient details. 40 image test regions are selected from each category of liver images-normal, cyst, benign and malignant. The features are extracted, subjected to feature selection and the classification processes.

A. Feature Extraction Methods

In this module 2statistical and 2 spectral based texture features are extracted from the test region selected from the ROI. The algorithms discussed in this paper are:

1) Grey Level Co-Occurrence Matrix Based Statistical Texture Features: This grey level co-occurrence matrix (GLCM) formulated by Haralick [7], offers information about the inter-pixel relationship, spatial grey level dependencies and the texture's homogeneity, periodicity and directionality of the underlying test region. This square matrix estimates the inter-pixel positioning and each cell carries the count of the number of times a pixel pair occurs as a function of two other parameters, the distance 'd' and the angle 'θ' between them. Generally the value of 'd' is fixed at 1 and θ is allowed to vary in steps of 45 degrees clockwise up to 180 degrees to get 4 such matrices completely describing the image region. From each of the GLCM 8 meaningful texture descriptors are extracted and thus we end up with 32 texture features initially.

2) Grey level run length matrix based Statistical Texture features: The grey level run length matrix formulated by Galloway [10] is another method of evaluating the image texture and has been a major descriptor of the shape-regularity, linearity of adjacent image-pixels. A set of consecutive pixels with same grey level, co-linear in a given direction constitutes a run. The run length is the number of pixels in a run. The Grey level run length matrix (GLRLM) is a 2D matrix computed from the underlying test region in which each element $p(i, j \mid \theta)$ gives the total number of consecutive runs of length j at grey level i in the direction θ. From this matrix almost 11 scalar parameters can be computed to analyze grey-level distribution for various textures.

3) Law's Spectral Texture Features: Law's 1D kernels are popular for classifying the different texture patterns based on homogeneity and energy [7]. A number of 2D masks are generated by convolving 5 such 1D kernels with each other heuristically. Each of these 1D kernels performs local averaging, edge detection, and spot detection and wave detection on the image region. The best 2D masks are convolved with the image test region and the horizontal energy information of the filtered image is used as a texture feature after normalization.

4) Gabor Wavelet's based Spectral Texture Features: Ahamedian et al [11] suggested that the Gabor wavelet coefficients reveal the localized frequency distribution of a signal or an image. Its frequency response is Guassian in shape and any noise is modeled as a sinusoidal interference. Thus Gabor filters are orientation, scale tunable edge and line detector that are highly frequency selective while displaying good resolution. 24 such Gabor filters of window size 10x10 formed at 4 different scales and 6 different orientations are applied on the image test region. The images are filtered using the Gabor filter banks, and First-order mean is identified as the best parameter to capture the texture homogeneity and uniformity.

B. Optimal Feature Selection

Each feature extraction method corresponds to number of texture feature descriptors, some of them being meaningful and the rest being redundant. The redundant data includes the possibilities of misclassification and hence must be removed. Blindly truncating some of the features affects the mean square error variance of the data set drastically. For large dimension features, Principal component analysis

(PCA) is a selection tool when the feature dimension is too high and graphical representation is not possible. PCA is a linear invertible mapping of the data from a feature space into separable patterns in the pattern space. This mapping

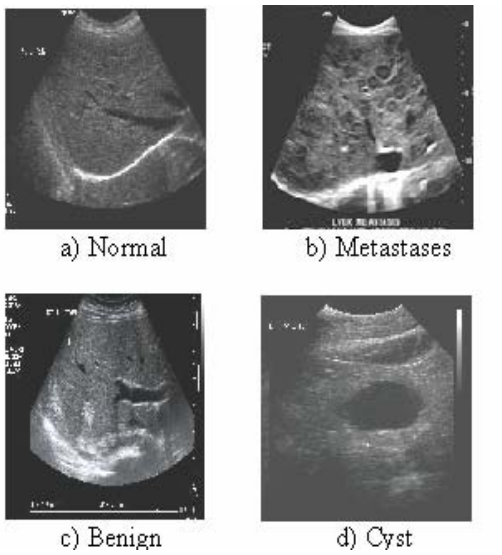

Fig. 1. Ultrasound Liver Images Used For Analysis

process transforms the feature vector by projecting the original data along the directions of greater variance. These projections, called the principal components (PC) are orthogonal and of reduced dimensions compared to the original data, since the overlapping data are eliminated. This rapidly reduces the mean square error variance to an optimal value. Thus, the complete texture information about these focal liver lesions could be obtained by combining the optimal features. This offers better description of the texture region in terms of homogeneity, regularity, directionality, and energy and frequency localization. Hence 2 sets of combined features are built by combining the automatic and manual selected features respectively for comparison.

III. Classification and Evaluation

In this study, 40 test regions from each lesion category of size 10x10 are taken. All the test images are pathologically tested and have fair quality. All 160-test image regions are subjected to the four-feature extraction process and the respective initial data set is collected. The PCA based dimension reduction process is carried out individually on the initial data set extracted using the 4 algorithms and the dimension reduction is shown in TABLE I. The first 2 principal components from each set are combined to form the set of automatic selected optimal features of length 8. This feature set is clustered using a k-means classifier into 4 disjoint classes. The percentage of the number of test image regions correctly classified into their respective classes is used as performance metric since initially there are 40 regions in each class. TABLE II summarizes the feature

TABLE I
PCA Based Dimension Reduction

Feature Extraction Method	Original Dimension	Reduced Dimension
GLCM	33	7
GLRLM	9	3
LAWS ENERGY	22	5
GABOR MEAN	24	5

values of the manually selected feature set. The *GLCM* energy, entropy is high for the cyst where neighboring pixels with similar grey levels leads to high values at certain cells of the matrix. Also, *LAWS* energy features are high for the cystic lesion as they are homogeneous. Instead the Gabor mean is very low for homogeneous region and high for benign lesion, as it resembles disturbed and noisy patterns. Similarly the *GLRM* long run low and high grey level emphasis features capture the nature of the cystic and benign primitive. For this combined set the back propagation network (BPN) classifier is constructed initially with 8 input nodes, 2 hidden layers with 10 nodes each and 4 output nodes with the following output encoding–'1000' for normal,'0100' for cyst, '0010' for benign and '0001' for malignant lesions respectively. The output layer is using competitive transfer function that produces a 1 for the winning neuron. All the input parameters are scaled suitably to avoid the bias caused by unbalanced features. The tan-sigmoid activation function is used at the network layers.

The network parameters such as number of hidden layers neurons, learning rate and momentum constant are generalized on the basis of minimum execution time at minimum sum squared error. Two hidden layers are used as the neurons in the first layer learn the local features and the neurons in the second hidden layer learn the global features for mapping the unknown input into the specific output region. Though started with equal number of neurons at the hidden layer, our network performance is optimal when first layer has 4 units and the second layer has 6 units. The initial weights and biases are set randomly within the minimum and maximum input range. The standard steepest descent error back propagation algorithm is used to train the network with adaptive learning rate and momentum based weight updates. 5000 leaning epochs is used for training the network. After repeated analysis the learning rate is fixed at 0.01and the momentum constant is fixed at 0.4. The network is trained and tested using jackknife procedure. The performance of BPN and K-means classifier is tabulated in TABLE III. On comparison to the PCA based k-means clustering, BPN network based classifier yields slightly high

rate of correct classification for cyst and malignant metastases images. The automatic feature selection through PCA does not increase the classification performance as expected but it reduces slightly the computing time. Though overlapping features are removed without affecting the data integrity using the PCA clustering, the BPN based classification using manually selected feature set is considered efficient. The manual selection of data set includes the process of scanning the entire data set for optimal features is voluminous, tiring, prone to errors and tedious. But still it results in a reliable efficient classification. From the experimental results the classification of the focal lesions based on the texture information using the set of optimal combined feature yields promising results.

IV. CONCLUSION

A multi-class multi-variant problem like classification of the focal lesions of the liver using ultrasound liver images is automated using the PCA and BPN approach. The performance of the classifier is expected to improve with a

TABLE II
MANUAL OPTIMAL FEATURE SELECTION

Optimal Features	FEATURE VALUES			
	Normal	Cyst	Benign	Metastases
GLCM-Energy	0.93± 0.007	1.36± 0.17	1.073± 0.08	0.905± 0.02
LCM-Entropy	0.049± 0.004	0.28± 0.8	0.13± 0.05	0.0338± 0.016
GLRLM-Long Run Low Grey-Level Emphasis	0.0262± 0.0016	1.6± 0.23	0.022± .0093	0.11±. 0.032
GLRLM-Long Run High Grey-Level Emphasis	0.621± 0. 3	0.8± 0.055	0.946± 0 .027	0.75± 0.029
LAWS-EE Mask	0.012 ± 0.0015	0.0524± .0068	0.0204± 0.0015	0.018± 0.0063
LAWS –EL Mask	0.069 ± 0.006	0.224± 0.0164	0.095± 0.006	0.018± 0.0517
Gabor Mean (Scale 2 Orientation 0)	0.8223± 0.40	0.4018± 0.202	2.39± 1.106	1.29± 0.62
Gabor Mean (Scale 3 Orientation 0)	0.0661± 0.04	0.1836± 0.101	0.798± 0.4012	0.394± 0.17

TABLE III
CLASSIFIER PERFORMANCE EVALUATION

Classifier Type	RATE OF CORRECT CLASSIFICATION (%)			
	NORMAL	CYST	BENIGN	METASTASES
K-means Clustering	70	87.5	77.5	88
BPN Network	75	93.5	80	90

Preprocessing operation to eliminate noise and improve the contrast there by improving the image quality.

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